International Journal of Basic and Applied Sciences, 14 (4) (2025) 242-249

International Journal of Basic and Applied Sciences

Website: www.sciencepubco.com/index.php/IJBAS
https://doi.org/10.14419/92vkkc31
Research paper

Intelligent Control of BLDC Motors Using Adaptive PID and ANN Techniques

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Received: July 6, 2025, Accepted: August 4, 2025, Published: August 9, 2025

Abstract

Brushless Direct Current (BLDC) motors are extensively used in modern applications such as electric vehicles, robotics, and industrial automation due to their high efficiency, precision control, and low maintenance. However, achieving consistent and accurate speed regulation under varying operating conditions remains a challenge with traditional fixed-gain PID controllers. This study proposes an intelligent control framework that integrates Adaptive PID (APID) and Artificial Neural Network (ANN) based control techniques for BLDC motor speed regulation. The APID controller employs a hybrid strategy combining Model Reference Adaptive Control (MRAC) and Self-Tuning Control (STC) to dynamically tune the controller gains based on real-time system parameters and reference tracking. Additionally, an ANN-based controller is implemented to learn and predict optimal control actions based on motor dynamics. A comparative simulation study using MATLAB/Simulink evaluates the performance of four control strategies: traditional PID, adaptive PID, ANN-based control, and a baseline without PID. Key performance metrics were analyzed. The results demonstrate that the APID controller significantly outperforms the traditional PID, achieving the fastest settling time and improved system stability under dynamic load variations. The ANN controller also delivers superior performance compared to conventional PID, but slightly lags behind APID in responsiveness. These findings suggest that adaptive control and intelligent learning-based strategies offer robust, efficient, and scalable solutions for advanced BLDC motor control systems.

Keywords*: Brushless DC Motor (BLDC); Adaptive PID Control; Artificial Neural Network; Speed Regulation; Real-Time Control*

1. Introduction

Brushless Direct Current (BLDC) motors have gained widespread adoption across various applications such as electric vehicles, robotics, HVAC systems, and household appliances due to their high efficiency, compact structure, and minimal maintenance requirements. These advantages make BLDC motors especially suitable for precision-driven applications where accurate speed control is essential [1]. However, maintaining stable and precise speed regulation becomes increasingly challenging under dynamic operating conditions, including varying loads and external disturbances. Traditional control methods, such as fixed-gain Proportional-Integral-Derivative (PID) controllers, often struggle to maintain optimal performance in such environments. These limitations typically result in issues such as overshoot, steady-state errors, and prolonged settling times, thereby compromising system reliability and responsiveness.

To address these challenges, APID controllers have emerged as a promising solution. Unlike conventional PID controllers with static gain values, APID controllers utilize real-time feedback mechanisms to automatically tune control parameters during operation [2]. This dynamic adjustment enables the system to respond effectively to parameter variations, load changes, and external disturbances. For instance, in applications where the motor is subject to sudden load shifts, adaptive controllers can recalibrate their responses almost instantaneously, ensuring rapid convergence to the desired operating conditions with minimal error. This adaptability is critical in applications demanding high reliability, responsiveness, and precision.

The strength of APID control lies in its ability to learn and adapt continuously based on the system's real-time behavior. By fine-tuning the proportional, integral, and derivative gains dynamically, the controller optimizes overall system performance [3]. This leads to faster transient responses, reduced overshoots, and enhanced stability, even in highly variable conditions. Furthermore, the adaptive nature minimizes the need for manual tuning, simplifying implementation and maintenance, while simultaneously improving energy efficiency and operational robustness [4][5].

Incorporating APID control into BLDC motor systems represents a significant evolution in motor control strategies. It effectively overcomes the limitations of traditional fixed-gain methods and delivers superior performance across a broad range of operating scenarios [6]. Moreover, as industries increasingly demand higher levels of automation, precision, and fault tolerance, the integration of intelligent, self-tuning control strategies such as APID will play a pivotal role in unlocking the full potential of BLDC motor-driven systems [7].

A. Gastli and M. M. Ahmed (2005) proposed an ANN-based soft-starter control system designed for voltage-controlled induction motor drives [8]. The system was validated through simulations and experiments, demonstrating a smoother motor starting process with reduced electrical and mechanical stresses compared to direct-on-line starting. The ANN model was trained on speed and torque data to accurately predict the appropriate thyristor firing angles, ensuring a smooth ramp-up of speed and torque. Experimental results showed minimal speed error (below 0.4%) between reference and actual values under varying load conditions, confirming the system's accuracy. The soft starter proved effective for industrial applications such as compressors, blowers, fans, and pumps, offering a reliable and stable open-loop control method without the need for additional sensors.

Tien-Chi Chen and Tsong-Terng Sheu (2002) introduced a robust speed control method for induction motor drives, utilizing a neural network-based predictive control scheme (NNPIC) combined with a load observer [9]. This approach adapts in real time to unknown motor dynamics and enhances the system's resilience to parameter variations and load torque disturbances. By employing a projection algorithm as the learning mechanism, the system autonomously adjusts control parameters, reducing sensitivity to non-linearities and disturbances. Experimental results compared the proposed NNPIC control scheme with conventional PI control, demonstrating superior speed response and faster recovery from load disturbances. The proposed scheme effectively handles system parameter variations and ensures stable performance under changing conditions. This innovative method highlights the benefits of neural networks in improving the adaptability and robustness of induction motor control, offering significant advantages over traditional PI-based controllers.

T. Li and J. Zhou (2019) presented a novel position-sensorless control method for BLDC motors, with a focus on low-speed operation [10]. The method introduces three algorithms: ZCP detection, speed calculation, and a compensation algorithm. Simulation results demonstrated effective ZCP detection with minor angle errors that decreased as speed increased. The back-EMF fluctuation was successfully corrected, ensuring stable motor performance under load. Experimental results confirmed the motor's stability, with commutation errors remaining below 5 degrees—even at rated speed and during dynamic speed changes. The method achieved less than 1.5% commutation error at low speeds, verifying its reliability and effectiveness for BLDC motor control.

Y. Liu et al. (2014) introduced a novel speed estimation algorithm for BLDC motors based on Model Reference Adaptive Control (MRAC), designed to enhance performance across a wide speed range [11]. The algorithm employs two regulators: one adjusts the back-EMF coefficient at high speeds, while the other compensates for stator resistance voltage division at low speeds, enabling stable operation even at very low speeds. Simulations conducted using Saber demonstrated that proper tuning of proportional and integral parameters (kp1, ki1, kp2, ki2) was crucial to prevent oscillations and ensure fast response times. Experimental results, obtained using a DSP controller and two BLDC motors, confirmed that the proposed algorithm significantly reduced speed oscillations at both high and low speeds compared to conventional methods. Additionally, the algorithm proved robust against variations in stator resistance and back-EMF coefficients, delivering reliable performance without requiring additional tuning for different motor types.

P. M. de Almeida et al. (2021) presented a robust discrete-time control strategy for variable-speed, low-inductance BLDC motor drives, validated through a prototype system using a DSP TMS320F28335 [12]. The proposed control ensures stable steady-state performance with a fast transient response, achieving a settling time of 0.3 ms with no overshoot or steady-state error. It also demonstrates resilience to voltage transients and back-EMF disturbances without requiring additional compensation. Tests involving a switch from robust feedback gains to those derived from pole placement and DLQR methods revealed system instability, confirming theoretical predictions. An outer speed control loop employing an IP compensator achieved a 2-second settling time without overshoot and successfully tracked a European driving cycle benchmark. The control strategy, which uses Linear Matrix Inequalities (LMIs) to compute feedback gains, ensures robust stability and high performance while reducing computational complexity, as confirmed by experimental results.

G. H. Jang and C. I. Lee (2005) introduced a novel winding method and inverter circuit for driving a BLDC motor, specifically prototyped for a hard disk drive (HDD) spindle motor [13]. The motor operates at speeds of up to 10,000 r/min, utilizing dual windings (main and auxiliary) to enhance starting torque. This dual winding configuration results in a 60% increase in starting torque compared to the main winding alone, particularly effective at speeds below 6,000 r/min. Beyond this threshold, the inverter automatically deactivates the auxiliary winding, enabling the motor to reach a maximum speed of 14,000 r/min. The design reduces startup time by 16.7% and improves efficiency at lower speeds. Experimental results validate the inverter's ability to switch between windings for optimal performance, making the system suitable for high-speed electromechanical applications and reducing power consumption during frequent startup operations.

T.-Y. Lee et al. (2016) compared an 8-pole/12-slot BLDC motor (BLDCM) with a 16-pole/12-slot surface-mounted permanent magnet synchronous motor (SPMSM), both powered by a 12 VDC source and designed for blower motor applications [14]. To minimize torque ripple and ensure consistent performance, the SPMSM employed parallel magnetization, whereas the BLDCM used radial magnetization. Identical design criteria—such as core dimensions and current density—were maintained to ensure a fair comparison. The SPMSM demonstrated a 12.8% increase in output power density and a 78% reduction in torque ripple compared to the BLDCM, due to its reduced stack size and improved phase back-EMF waveform. A delta-winding SPMSM prototype was manufactured, and its experimental results closely matched findings from 3D finite element analysis (FEA), showing only a 5.8% efficiency difference attributed to mechanical losses. Overall, the SPMSM design delivered superior performance in terms of power density and torque smoothness.

M. Algreer et al. (2011) explored the trade-off between dynamic performance and computational complexity in adaptive control systems, proposing two solutions: the Least Mean Squares (LMS) algorithm for reduced computational burden and the Dichotomous Coordinate Descent Recursive Least Squares (DCD-RLS) algorithm for enhanced dynamic performance [15]. Although DCD-RLS is more computationally intensive than LMS, it remains more efficient than traditional RLS methods. A hybrid DCD-RLS: LMS control scheme was introduced to strike a balance between performance and complexity by replacing the second-stage DCD-RLS with an LMS-based Predictor Error Filter (LMS-PEF), thereby maintaining good system response without significantly compromising convergence time or control accuracy. Simulation and experimental results demonstrated that the hybrid system achieved excellent performance, albeit slightly less dynamic than the original two-stage DCD-DCD scheme—making it suitable for applications where computational efficiency is critical. Unlike prior ANN-based soft-starter or induction-motor studies that focus on start-up transients or non-BLDC platforms, and unlike sensorless/observer works that emphasize commutation and estimation accuracy, our contribution is a control-layer hybrid adaptive strategy for BLDC speed regulation that combines MRAC and STC to tune PID gains online under load and parameter variations. In contrast to robust fixed-gain designs, the proposed MRAC–STC framework adapts to drift and disturbances in real time while retaining the transparency and deployability of PID control. Furthermore, we benchmark APID against an ANN controller and a fixed PID within a single

Simulink/OPAL-RT workflow using common operating conditions and application-relevant metrics (settling time, overshoot/undershoot). This unified, quantitatively grounded comparison—together with real-time validation—highlights the practical novelty of an adaptive, resource-light controller suitable for embedded EV/industrial drives. The adaptive PD+I controller applied to DC-DC converters further confirmed the feasibility of the DCD-RLS algorithm in achieving fast parameter convergence and error minimization. Notably, the integral controller briefly amplified oscillations to enhance prediction and identification accuracy, making this approach well-suited for real-time control and system identification tasks.

2. Methodology

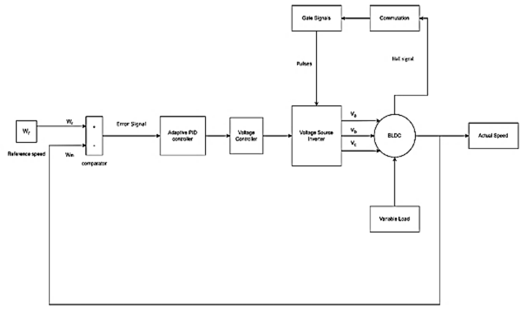

Fig. 1: Block diagram of the adaptive controller for a BLDC motor

Figure 1 illustrates the adaptive control architecture for a BLDC motor, designed to maintain the desired motor speed under varying load conditions. The system incorporates an APID controller to dynamically regulate the motor speed based on real-time feedback. An APID controller is designed to adjust its Proportional, Integral, and Derivative gains in real time, enabling improved control of systems such as BLDC motors, which often operate under varying loads and dynamic conditions. BLDC motors are widely used in applications like electric vehicles, drones, and industrial machinery due to their high efficiency, reliability, and precise control capabilities.
The operation of a BLDC motor is governed by its unique construction and electronic commutation strategy. Unlike conventional brushed motors, BLDC motors use electronic switching to control the phases of the stator windings, which improves efficiency and reduces maintenance requirements. The motor's behavior can be modeled using a transfer function, typically expressed as:

$$\text{Transfer function} = \frac{16*s}{s^2+4*s+16} \tag{1}$$

In this expression, K represents the motor gain constant, and ω_n denotes the natural frequency. This transfer function characterizes the motor's response to changes in input voltage and serves as the foundation for designing control strategies.
To implement an APID control scheme for a BLDC motor, a hybrid control strategy is employed by integrating Model Reference Adaptive Control (MRAC) and Self-Tuning Control (STC). This hybrid approach provides a highly adaptive and robust framework. The MRAC component defines a reference model that represents the desired motor behaviors, such as a specific speed or torque trajectory, and ensures that the actual motor output closely tracks this reference. By continuously comparing the actual and reference responses, MRAC adjusts the controller parameters (i.e., PID gains) in real time to minimize the tracking error. This enables accurate performance even under variable operating conditions.
Simultaneously, STC enhances the system by dynamically estimating and adapting to the motor's internal parameters, such as winding resistance, inductance, and back-EMF. These parameters may fluctuate due to external factors like temperature changes or load variations. STC uses real-time system identification techniques to monitor these changes and modify the PID gains accordingly. For example, if an increase in winding resistance is detected due to heating, STC compensates by recalibrating the gains to maintain control stability and performance
Figure 2 illustrates a hybrid control architecture that integrates Model Reference Adaptive Control (MRAC) with a Self-Tuning Control (STC) mechanism to form an APID control strategy for a BLDC motor drive system. This configuration is designed to ensure precise and robust performance in the presence of system uncertainties, external disturbances, or parameter variations. The combination of MRAC and STC yields a control system that simultaneously achieves adaptive trajectory tracking and real-time gain tuning. MRAC ensures conformity with the desired reference behavior, while STC responds to internal motor dynamics. This synergy results in a control framework that is both robust and precise, capable of withstanding external disturbances (e.g., load shifts) and internal degradations (e.g., component aging or wear). Consequently, the system remains efficient and responsive without the need for manual retuning, making it ideal for high-performance applications such as electric vehicles, robotics, and industrial automation.

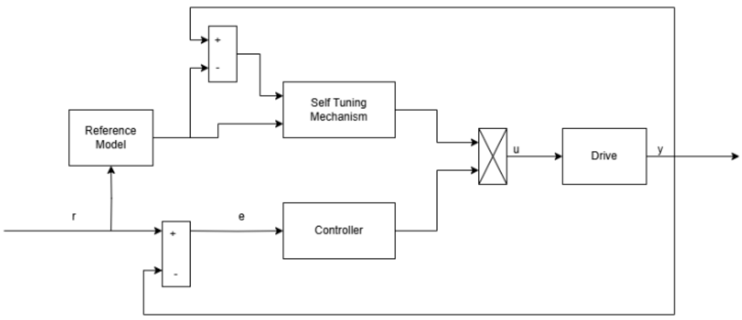

Fig. 2: Block diagram of MRAC-STC-based adaptive PID control for BLDC motor

2.1 Results and Discussion

Figure 3 presents the experimental hardware setup used to validate the adaptive control strategies for BLDC motor control using real-time simulation via the OPAL-RT platform.

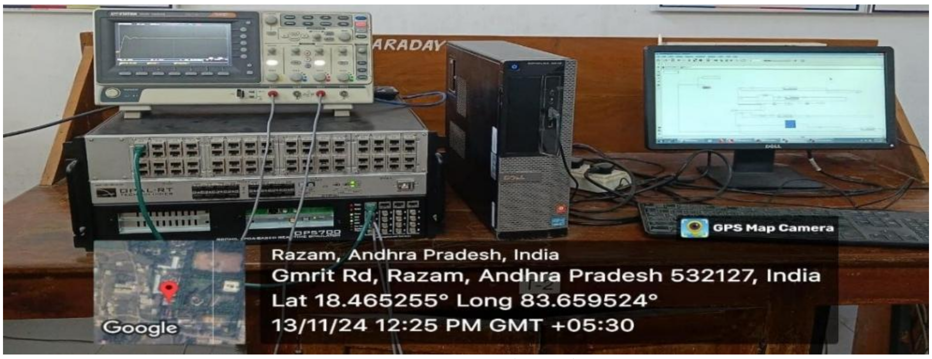

Fig. 3: OPAL-RT Experimental Setup

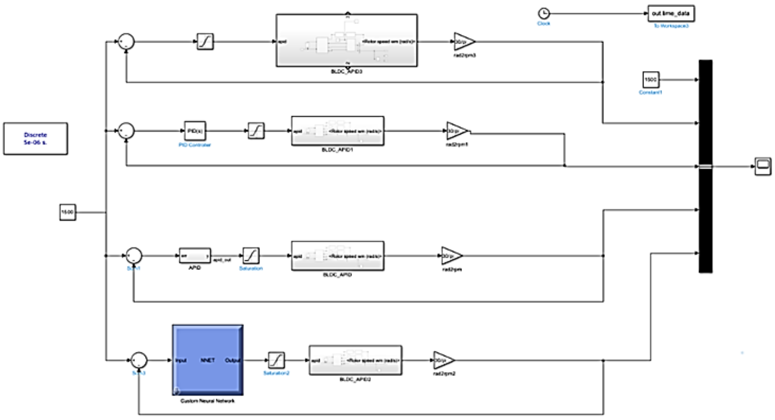

Fig. 4: Simulink Model for BLDC Motor Control Using Different Strategies

Figure 4 illustrates a comprehensive Simulink model used to compare multiple control strategies for a BLDC motor. The system is designed to evaluate and visualize the performance of each control method under identical operating conditions. The first section (top branch) shows the motor running without any control loop, serving as a baseline or open-loop configuration for reference. The second section implements a conventional PID controller. The desired speed input is compared with the actual motor speed, and the resulting error is processed through a fixed-gain PID controller. The output drives the BLDC motor model (BLDC_APID3), providing a basis for evaluating standard control effectiveness. The third section features an APID controller, which dynamically adjusts its PID gains in real time based on system feedback. This enhances adaptability in the presence of disturbances or parameter variations. The motor behavior under this strategy is modeled in the BLDC_APID1 block. The fourth section integrates a Neural Network (NNET)-based controller. The neural network is trained to generate optimal control signals based on real-time motor parameters. Its output passes through a saturation block to limit extreme control actions before being applied to the motor (BLDC_APID2). Each of the control strategies routes its output to a common multiplexer for unified comparison, and the results are logged using a scope and workspace output for further analysis.

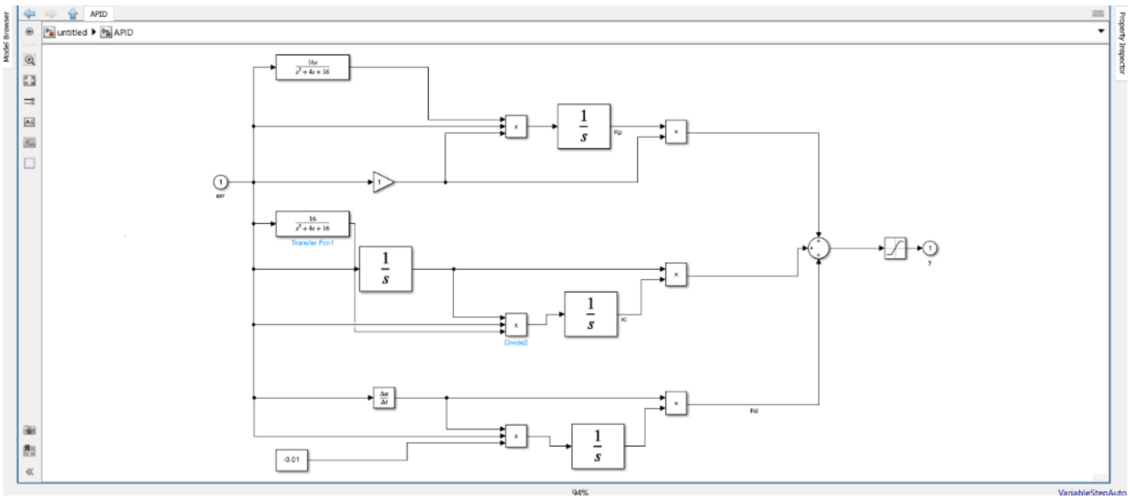

Fig. 5: Simulink-Based Adaptive PID Controller Architecture

Figure 5 shows the Simulink implementation of an APID controller designed to regulate the output y of a dynamic system in response to a reference input. The objective is to maintain the system's output close to the desired value, even in the presence of system disturbances or parameter variations.

The model includes the following components: A transfer function block representing the motor dynamics, given by $\frac{16*s}{s^2+4*s+16}$. This block defines the plant being controlled—presumably a BLDC motor or similar second-order system. An error signal is computed by subtracting the actual output from the desired input. This error is processed through three parallel control paths representing the Proportional (Kp), Integral (Ki), and Derivative (Kd) components of the PID controller. A gain block (Kp, Ki, Kd) that can be adaptively modified. An integration block (1/s) to implement the integral and derivative actions. A summation block that combines all control actions to form the controller output. A divider block is included in the integral path, which likely enables adaptive scaling or tuning of the integral gain based on real-time system parameters. The combined control output is then fed to the plant (transfer function), and the resulting output y is looped back to the comparator, closing the feedback loop. A saturation block is applied at the end to constrain the output within a safe or operational range, preventing signal overflow or instability.

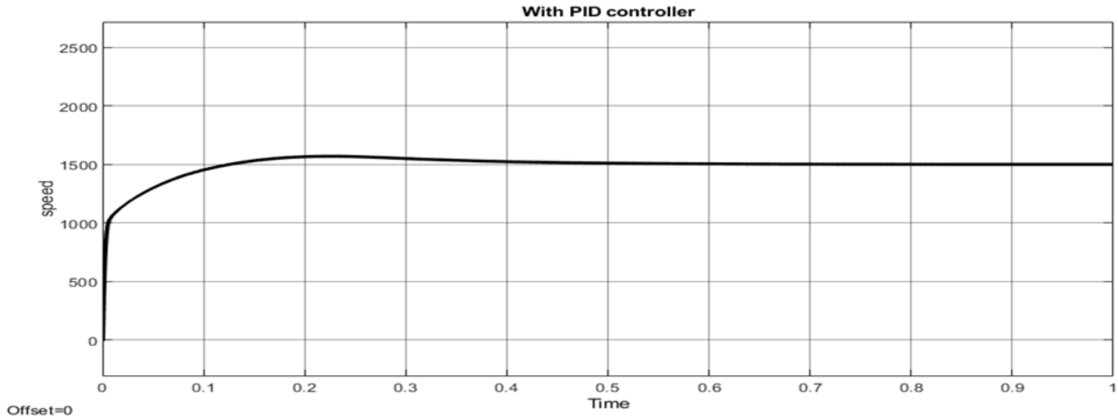

Fig. 6: Speed Response of BLDC Motor with Conventional PID Controller

Figure 6 displays the closed-loop speed response of a BLDC motor controlled via a conventional PID controller. The plot illustrates how the motor's speed evolves (x-axis: Time in seconds, y-axis: Speed in RPM or units proportional to speed) after receiving a step reference input. The response exhibits minor damping and stabilizes around the reference speed by ~0.05 to 0.06 seconds, achieving a settling time of ~54.28 ms.

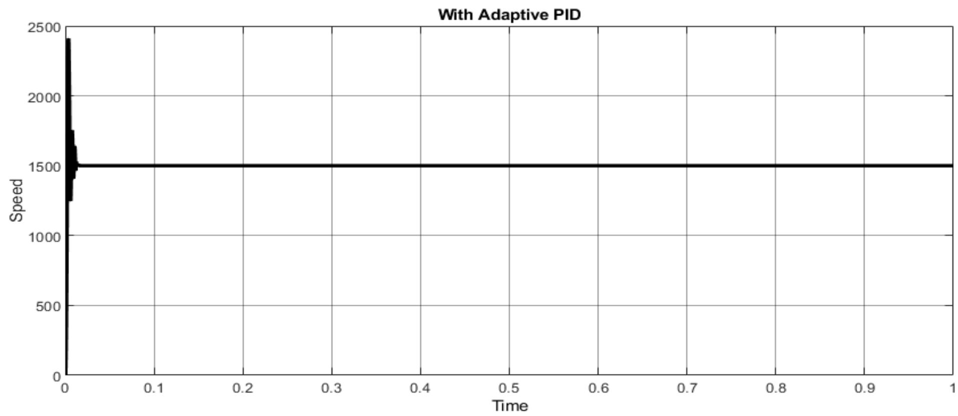

Fig. 7: Speed Response of BLDC Motor Using Adaptive PID Controller

Figure 7 illustrates the speed response of a BLDC motor controlled using an APID controller, which dynamically adjusts its proportional, integral, and derivative gains in real time to optimize system performance. Despite the initial fluctuation, the motor speed settles quickly and precisely at the reference value (around 1500 units) within just 10.248 ms, far outperforming traditional PID control in terms of speed. The APID controller excels in speed and responsiveness, making it ideal for applications where rapid control adjustments are required.

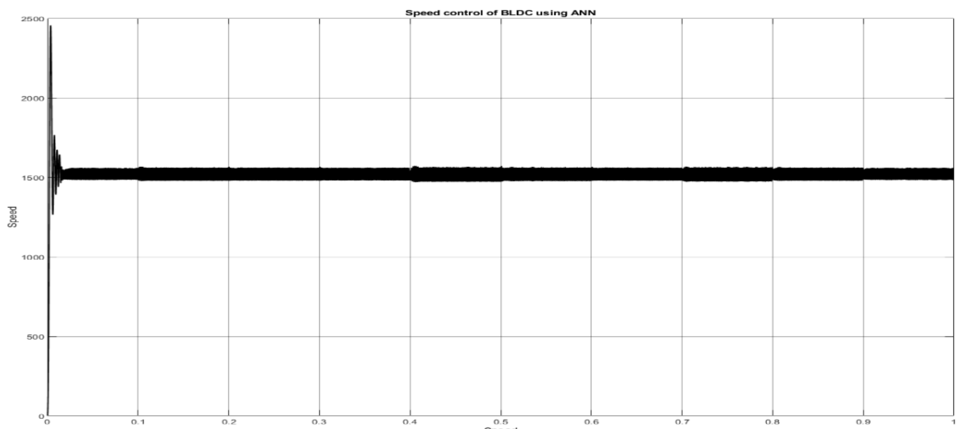

Fig. 8: Speed Response of BLDC Motor Using ANN-Based Controller

Figure 8 shows the speed-time response of a BLDC motor controlled using an ANN-based controller. This approach uses a trained neural network to generate control signals based on real-time feedback, enabling intelligent, nonlinear control of the motor dynamics. The ANN controller reaches the reference speed in ≈19.425 ms and demonstrates strong dynamic performance, although it is slightly slower than the adaptive PID controller. The ANN maps present-time features to a control increment $\Delta u(t)$, which is integrated and then saturation-limited to yield the PWM duty command $u(t)$. The trained ANN is inserted into the same Simulink plant with the identical non-idealities used in data generation.

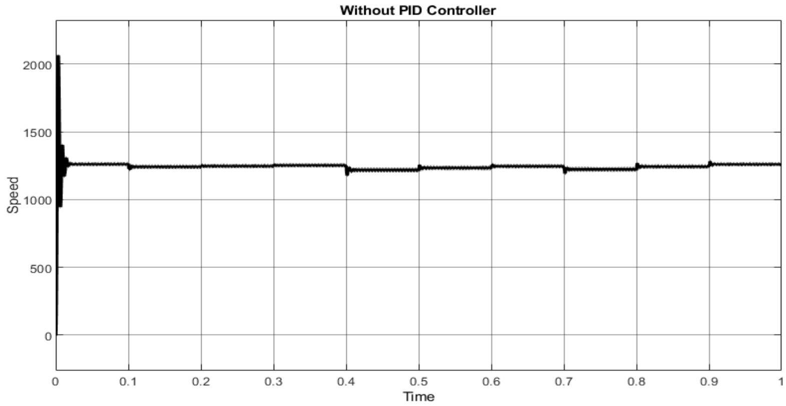

Fig. 9: Speed Response of BLDC Motor Without PID Controller

Figure 9 illustrates the open-loop speed response of a BLDC motor operating without any PID or intelligent control mechanism. This setup reflects the raw behavior of the system under a step input, revealing its natural dynamics and limitations in the absence of closed-loop feedback regulation. While the oscillations reduce over time, the response does not converge smoothly to a steady value, indicating uncontrolled dynamics. The system fails to exhibit a clear settling behavior, which is critical for precision applications. Minor sustained oscillations around the 1200–1300 RPM range can still be seen even after 0.9 seconds, highlighting the need for a feedback-based control strategy.

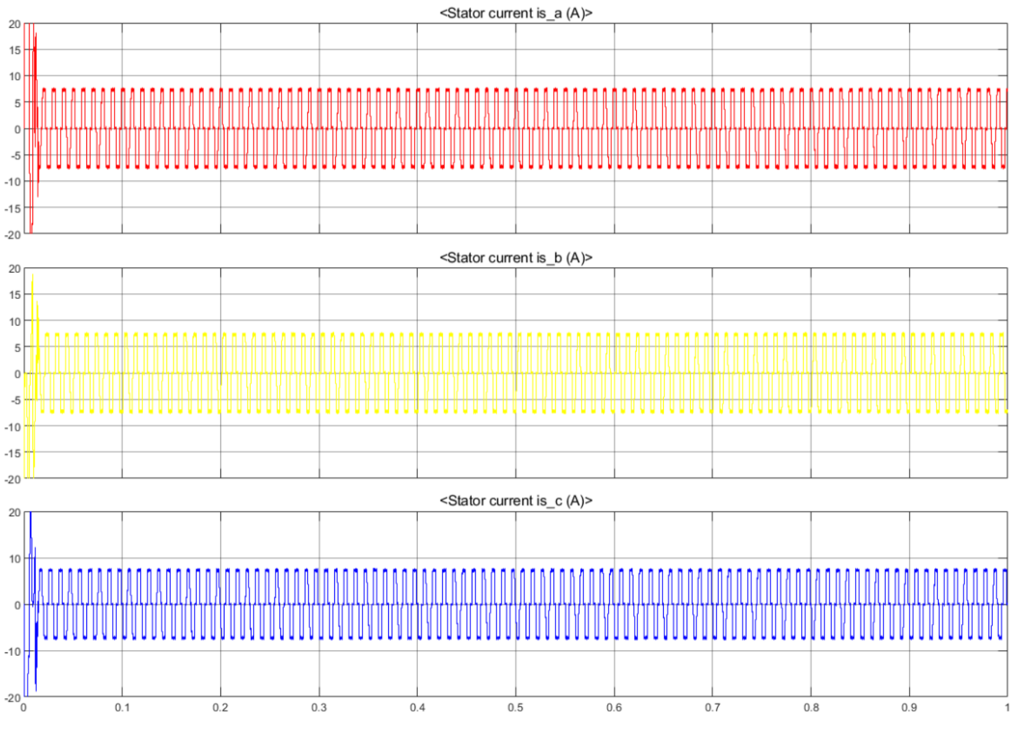

Fig. 10: Stator Phase Currents (i_a, i_b, i_c) of the BLDC Motor

Figure 10 displays the three-phase stator currents of a BLDC motor. The currents exhibit a quasi-trapezoidal waveform, which is characteristic of BLDC motors due to electronic commutation and trapezoidal back-EMF. The three-phase currents are symmetrical and balanced, maintaining a 120° electrical separation. This ensures consistent torque production and smooth motor operation. The stator current profiles confirm that the BLDC motor is operating under healthy and stable conditions after initial start-up. The waveform integrity and balance across the three phases validate the controller's effectiveness in managing commutation and current distribution. Proper current shaping is essential for reducing torque ripple and enhancing motor efficiency.

Table 1 presents a comparative analysis of four control strategies—no controller, PID, Adaptive PID, and ANN—based on key performance metrics such as settling time, rise time, overshoot, undershoot, and peak overshoot for a BLDC motor system.

In the case of the system without a PID controller, it remains uncontrolled, exhibiting an extremely high overshoot (123.36%) and no defined settling time, indicating instability and poor regulation.

The PID controller provides moderate control, with a low overshoot (4.737%), fast rise time (62.102 µs), and an acceptable settling time (54.28 ms).

The APID controller offers the fastest settling time (10.248 ms) and quick rise time, thanks to real-time gain tuning. However, the overshoot (60.484%) and undershoot (17.199%) are relatively high, suggesting aggressive control behavior.
The ANN controller balances adaptability and learning capability, with a settling time of 19.425 ms and a rise time comparable to that of the APID controller. It exhibits slightly higher overshoot (57.937%) and undershoot (18.926%) but ultimately stabilizes the system reliably. Based on the observation, the APID controller provides the fastest stabilization, making it ideal for dynamic environments, while the ANN controller demonstrates intelligent control with strong adaptability, albeit slightly less precise than Adaptive PID.

Table 1: Performance Comparison of Different Control Strategies for BLDC Motor

Controllers	Settling Time (ms)	Rise Time (ms)	Overshoot (%)	Undershoot (%)	Peak Overshoot
Without a PID Controller	---	0.576	123.360	4.906	2066
With PID Controller	54.28	0.0621	4.737	2.001	1570
With an Adaptive PID Controller	10.248	1.430	60.484	17.199	2412
With ANN Controller	19.425	1.389	57.937	18.926	2457

2.2 Scientific Insight and Implications

The results show that an adaptive PID (MRAC–STC) controller delivers the fastest stabilization under dynamic loads and parameter drift, while an ANN controller is a viable alternative when nonlinearities and unmodeled effects dominate and a data-driven policy is acceptable. From a deployment perspective, APID offers deterministic timing, small footprints, and transparent tuning for MCU/DSP targets typical of EV and industrial drives, whereas ANN-based control may improve nonlinear handling at the cost of training data curation and validation under drift. Given the observed speed–overshoot trade-off, we complement speed metrics with stress proxies (peak current, I^2t, di/dt) and recommend software-only operating practices—set-point ramping, conservative adaptation schedules, and anti-windup—to confine transient stress without hardware changes. These considerations make the proposed approach directly actionable for EV traction cycles and factory automation, where fast recovery from disturbances must be balanced against thermal/mechanical longevity.

3. Conclusion

The comparison of different control strategies based on performance metrics—particularly settling time—reveals significant variations in system stabilization capabilities. When operating without a PID controller, the system exhibits undefined settling behavior, indicating instability or sustained oscillations. This makes it unsuitable for precision-driven applications. The implementation of a conventional PID controller results in a marked improvement, with the system achieving a settling time of 54.28 ms. This demonstrates the effectiveness of fixed-gain PID control in managing system dynamics through proportional, integral, and derivative actions. However, it is comparatively slower than more advanced techniques. The APID controller delivers the best performance, achieving a significantly lower settling time of 10.248 ms. This improvement highlights its ability to dynamically adjust control gains in real time based on system conditions, making it highly effective in rapidly changing or uncertain environments. The ANN controller, while not as fast as the APID controller, also shows a substantial performance gain, with a settling time of 19.425 ms. The ANN controller handles complex, nonlinear dynamics but may provide less real-time adaptability than the APID scheme. The APID controller emerges as the most effective solution for achieving fast and stable control in dynamic conditions. The ANN controller, though slightly slower, still outperforms traditional PID control and represents a strong alternative for systems requiring intelligent, learning-based adaptation.

Acknowledgement

The authors gratefully acknowledge GMR Institute of Technology (GMRIT), Rajam, for providing access to the OPAL-RT real-time simulation facility, which was instrumental in conducting the experimental validation of this research work.

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